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Review Article

Assisted Living System: A Review of 25 Years of Research

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Abstract *- Increased population and globalization cause humankind to search for worldwide job opportunities and better areas to live in, leading to the change in family structures. This change in the family system increases the loneliness of older adults. There are significant demographic changes across India and the World. According to the Indian population census-2011, the aging population in India is projected to rise to 19 % in 2050. A demographic survey by the World Health Organization also projects an increasing world elderly population of up to 2.1 billion in 2050. In the upcoming days, the aging population and their healthcare system implementation will be a major challenge. To face this challenge, the assisted living system (ALS) will be helpful. ALS comprises different technologies and methodologies. These methodologies and technologies aim to create an ingenious environment for incapacitated and aged people. This paper reviews significant research on ALS in the last 25 years. The authors found more than 600 IEEE research papers on ALS. Studying these papers author discusses ALS, ALS types and techniques, and existing work on ALS in the last 25 years. This paper will be useful to know the opportunities and scope for further research in ALS.*

Keywords *- Assisted Living System, Activity recognition, Computer vision, Context awareness, Wearable sensors.*

1. Introduction

The increasing aging population is a global phenomenon. Life longevity, a declined birth rate, and improved healthcare systems are reasons for the aging population [7]. Worldwide, the increasing aging population is introducing major challenges to our society. Social isolation, loneliness, and health care conditions are major challenges in an aging population. It is necessary to overcome these challenges and find ways to assist incapacitated and aged people to live independently [6]. Further sections in an Introduction present statistics on the increasing population in India and World and their respective consequences.

1.1. Ageing population in India

The population census 2011 India expounds on demographic changes in India [1]. These demographic changes can be classified into urban and rural areas. In urban areas, 30.6 million aging population lives, whereas 73.3 million aging population resides in a rural area. The total aging population is 103.9 million. It is 8.58% of the total population in India. In 1951 the rise of the aging population was 5.5%, and in 2011 it was observed at 8.58%. The aging population in India has projected a rise of up to 19% in 2050. The mentioned data suggest a rapid rise in the aging population in India. The aging population in the World is also increasing as in India [1].

1.2. Ageing population in World

The United Nations report on the aging of the world population in 2017 [2]. It gives us an idea about demographic changes throughout the World. According to this report, in 1980, the World's aging population aged 60 years or over was 382 million. In 2017, the World's aging population was 962 million, which is more than double that of 1980. In 2017, the World's Aging population was projected to be approximately 2.1 billion in 2050. The aging population is rising in developed countries compared to developing and undeveloped countries. According to statistics, 33 percent of the elderly live in Japan, while 28 percent live in Germany and Italy. In Finland, 27% of the total population is over 60. In 2030, World's aged population is projected to be up to 16.5% of the total world population. It is quite high. The mentioned data suggests the rapid pace of the aging population in the World [2].

The aging population comes across health care problems like Osteoarthritis, Stroke, and Dementia. These type of diseases increases the dependency of incapacitated and aged people. A degenerative joint disease, Osteoarthritis (OA), is common in older adults above 60 years. It causes gradual loss of articular cartilage, synovial inflammation, and osteophyte formation. OA is India's most common joint disease, with 22% to 39% dilation. The effect of OA increases with age. Nearly 45% of women aged over 65 years have osteoarthritis symptoms. 70% of women aged over 65 years have osteoarthritis radiological evidence. Knee pain due to OA causes limitations in the mobility and functioning of older adults. Clinical research has found adverse psychological effects in older adults [75]. Stroke is also one of the diseases common in older adults. Also known as cerebrovascular accident. The probability of a cerebrovascular accident increases with age in both men and women. 50% of stroke survivors are over age 75, and 30% are over age 85. It is projected that 80% of stroke cases will occur worldwide in developing countries [3]. Like stroke, dementia is also a challenge to the healthcare system. World health organization report says that 50 million people have dementia in the World. Each year 10 million new dementia patients get added. It is projected that there will be 82 million dementia patients in 2030 and 152 million in 2050 [4]. Stroke and dementia statistics indicate an upward rise in respective health care problems. With the above discussion, the major consequences of the increased aged population for older adults are summarized below:

***Increased Diseases*:** Older adults are more likely to suffer chronic diseases such as stroke and dementia. As these diseases have more impact on aged people, the number of respective patients will be increased.

***Increased dependency*:** Normally, dependency increases in the aging population due to lowered body capacity and chronic diseases. It hampers the capability of doing daily work for incapacitated and older adults.

Lack of caretakers: With an increased aging population, there will be more requirements for caretakers for incapacitated and older adults in the distant future. As the aging population increases, there will be a shortage of caretakers.

***Increased indoor accidents*:** Older adults have two times more probability of having a fall while walking. Situations like stroke and sudden falls can increase indoor accidents.

Social isolation of older adults: Rise in nuclear family, loneliness, and chronic diseases will restrict most older adults from being social.

***Health care cost*:** Increased aging population, shortage of caretakers, and shortage of health care resources will increase health care costs in upcoming days.

Considering the above consequences, there is a need to develop technology that can help people with disabilities and the elderly. An assisted living system is a technology that helps incapacitate older adults to live independently [15]. Over 25 years ago, in 1995, Parris Wellman et al. [5] made a significant effort in the assisted living system with the construction of wheelchairs with legs for people with mobility impairments. Since the time, different researchers have contributed to assisted living systems with different methodologies, devices, and applications. The primary aim of this article is to investigate significant research and development related to the assisted living system over the last 25 years (1995-2020)

There are four sections in this paper. The first section depicts statistics on the growing elderly population and the need for ALS. The second section briefly overviews an assisted living system, technological advancement, ALS type, and techniques. The third section is a Discussion and findings section; here, significant samples of published work based on technological advancements and types of ALS in the last 25 years are discussed. It gives an idea about hardware, Sensors, algorithms, and applications in ALS. The authors have drawn short findings for each type of ALS with the samples of published work and other relevant literature. The fourth section concludes the ALS review using referred literature and short findings on each type of ALS. The conclusion gives us an idea of overall findings and future direction in ALS. This paper simply provides an overview of ALS developments. It is not intended to critique the existing work rigorously.

2. Assisted Living System

The assisted living system integrates electronic systems, methodologies, information, and services to decrease the dependency of incapacitated and aged people. It guarantees their safety, privacy, and convenience for everyday living activities. It focuses on end-users assisting their living environment for a self-determined lifestyle [8].

Fig. 1 Key aspects of assisted living systems

Assisted living system (ALS) includes wearable devices, computer vision applications, wireless sensor networks, sensors, computers, desktop software applications, and mobile applications, according to end-user requirements.
ALS has some aspects, as in Figure.1. These aspects support end-users in their homes, communities, and workplaces.
It ensures health and safety, social inclusion, entertainment & leisure, mobile services, safety and security, and activity management for incapacitated and older adults in different circumstances with different techniques [9]. ALS has been developed gradually. It is explained by technological advancement.

2.1. Technological Advancement

The assisted living system has a progressive scope with day-by-day technological advancements. Different technologies are accumulated under ALS. These technologies hinder people from living independently. It has shown advancements from low-tech devices like walkers to high-tech devices like smartphone-based ALS [69]. ALS has gradually progressed from 'activity of daily living' providing specific task support to 'ambient systems' providing multiple tasks in living areas with converged technologies. Technology advancements in ALS are divided into three generations of technologies.

- First-generation: Wearable devices
- Second generation: Home sensors
- Third generation: Converged technology

According to the UK model, these technologies are called 'telecare' [70], [71].

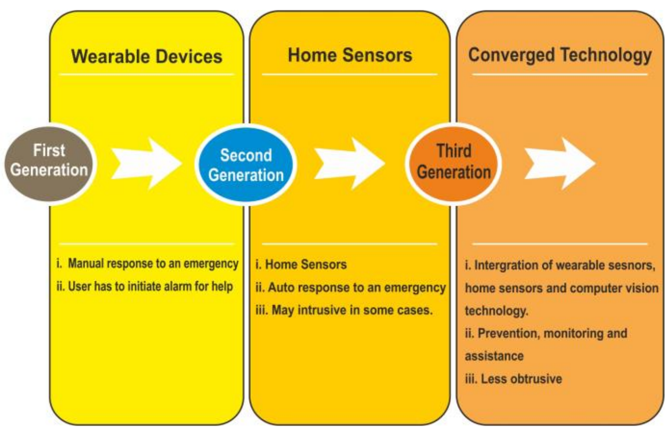

Fig. 2 Generations of assisted living systems

2.1.1. First-generation: Wearable devices

As shown in figure 2, the First generation of ALS includes wearable devices in alert systems. These wearable devices were in the form of pendants or alarm buttons. In case of emergency, incapacitated persons had to initiate wearable alert systems. 'LifeCall' was an example of first-generation ALS. It was creating a 'fall' alert. It increased public awareness of ALS. But the need for manual initialization of alerts was its major drawback [72], [73].

2.1.2. Second generation: Home sensors

The second generation of ALS included home sensors in the living area. This generation encompassed Hazard detection, auto-response, and alert system. It was inclined towards more automation. This system advanced from specific tasks to multiple tasks with an increased number of sensors. Smart home-based ALS is a good example of the second generation. But in some cases, intrusiveness was one of the drawbacks of the second generation [71], [72], [73].

2.1.3. Third generation: Converged technology

In the current third generation, different technologies are converged together. It integrates wearable devices, sensors, artificial intelligence, and computer vision systems. It not only detects hazards and generates auto-response but also monitors, prevents, and takes corrective action in a real-time situation. Context-awareness of real-time situations is a major advantage of current-generation ALS. Computer vision-based smart home ALS is the best example of third-generation ALS. It is less intrusive as compared to other ALS generations [72]. The next section explains the types of assisted living systems from all generations.

2.2. Types of Assisted Living System

As shown in Figure.3, There are six types of the assisted living system.

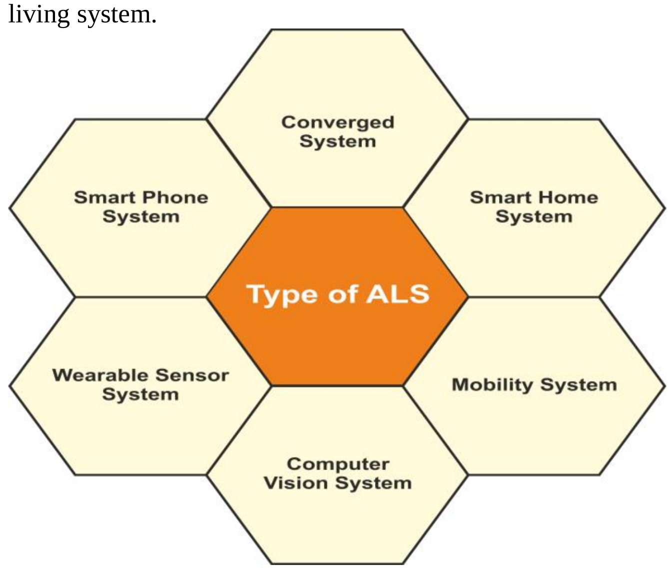

Fig. 3 Types of assisted living system

2.2.1 Mobility based ALS

Diseases like osteoarthritis limit the mobility and functioning of older adults. Mobility-based ALS is used to overcome this problem. It mainly includes wheelchairs. Stair-climbing wheelchairs [51] and wheelchairs with legs [43] are some of the valuable research in an Assisted Living system for elderly and incapacitated people.

2.2.2. Computer vision-based ALS

This type of ALS track and monitor lonely living older adults. Features like human activity recognition, fall detection, and anomaly detection using a computer vision system help to generate alerts in case of an emergency. Different cameras like depth cameras, RGB Camera, RGB-D Camera, IR Camera, and Vision cameras are used in Computer vision-based ALS. Their specifications vary according to the manufacturer and their applications.

2.2.3. Wearable sensor and smartphone-based ALS

Sensors used for wearable sensor-based ALS are summarized in Table. 1. These are widely used for applications like fall detection, health care condition monitoring, Location identification, and event-based alert system.

Table 1. Sensor used in wearable sensor-based ALS

S.n.	Sensors	Measurement	Data format
1.	Electro-Encephalogram	Brain Activity	Categorical
2.	Galvanic Skin Response	Perspiration	Numeric
3.	Glucometer	Blood Glucose	Numeric
4.	ECG	Cardiac Activity	Categorical
5.	Pressure	Blood Pressure	Numeric
6.	Thermal	Body Temperature	Very Low
7.	Gyroscope	Orientation	Numeric

It is used to identify user mobility, location, and various activities. Technological advances in Micro electromechanical Systems Technology (MEMS) and epidermal electronics have made efficient and user-friendly healthcare sensor technology [77].

Sensors used for smartphone-based ALS are summarized in Table. 2:

Table 2. Sensors used in smart home-based ALS

S.n.	Sensors	Measurement	Data format
1.	Ambient light sensor	Ambient light	Categorical
2.	Pedometer	Step count	Numeric
3.	Magnetometer	Direction	Categorical
4.	Thermometer	Temperature	Numeric
5.	GPS	Location co-ordinates	Numeric
6.	Accelerometer	Acceleration	Numeric
7.	Gyroscope	Orientation	Numeric

The sensors in the smartphone are mostly used to track health conditions, localisation, and fall detection of older adults. However, wearable sensors and smartphone-based ALS have advantages, although it has some limitations. Older adults find wearable sensors and smartphones inconvenient to carry all the time.

2.2.4 Smart home-based ALS:

It's a typical house with intelligent systems, sensors, and actuators. Data from these intelligent systems, sensors, and actuators are used to analyze and obtain rich context information. The list of sensors used in this type of ALS is given in the table.3 [15]. Smart home-based ALS utilizes sensors and electronic devices for decision-making and automation to provide comfort for the inhabitants. As its name suggests, smart home-based ALS is designed for in-house applications only. Its cost may vary according to the application and cost of sensors.

Table 3. Sensors used in smart home-based ALS

S.n.	Sensors	Measurement	Data format
1.	Gas sensor	Gas level	Categorical
2.	Level sensor	Level	Categorical
3.	Humidity sensor	Humidity	Numeric
4.	Passive Infrared Motion Sensor	Motion	Categorical
5.	pH sensor	pH level	Numeric
6.	Radio Frequency Identification	Object Information	Categorical
7.	Turbidity	Turbidity level	Categorical
8.	Microphone	Activity	Sound
9.	Proximity sensors	Existence	Categorical
10.	Ultrasonic	Existence	Categorical
11.	Pressure	Pressure on chair/floor	Numeric
12.	Level sensor	Level	Categorical
13.	Camera	Activity	Picture

2.2.5. Converged technology-based ALS

The convergence of more than one technology for a common application is called Converged technology. Converged technology-based ALS is a third-generation ALS; it converges all types of ALS and respective technologies per the end-users requirement. It is equipped with Context-awareness, computer vision, Artificial intelligence, electronic devices, and the Internet of things.

2.3 Assisted Living System Techniques

Different computational techniques and algorithms support assisted living system tools. These computational techniques and algorithms are named as per ALS applications. Like Anomaly detection, Context modelling, Activity recognition, planning, and Location identification [15]. It is shown in figure.4.

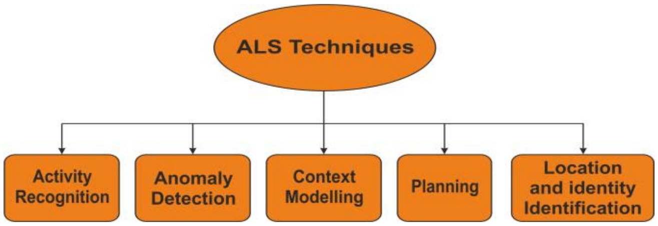

Fig. 4 Assisted living system techniques

In this section, a review of the significant assisted living system techniques is presented

2.3.1. Activity Recognition

Human activity recognition (HAR) is the most important component in an assisted living system. It is used to recognize human activity patterns. Sensors such as wearable, ambient, and Camera/Thermographic devices are utilized for human monitoring and Recognition. Output data type varies according to the type of sensors. Like Wearable sensors, e.g., gyroscope, accelerometer produces time series data. Ambient sensors, e.g., humidity and motion, produce categorical or numerical data. Camera/ Thermographic devices produce an image or video as output data.

2.3.2. Anomaly Detection

An abnormal living pattern is an unusual and undesirable behavior resulting in impairment in the individual's functioning. Anomaly detection deals with finding an abnormal living pattern. Important techniques used for anomaly detection are information-theoretic, clustering-based, and statistical methods [30]. These techniques are based on similarity, rules, and temporal relation discovery. Anomaly detection is essential to detect emergency medical conditions and hazardous situations in an assisted living environment.

2.3.3. Context Modelling

In the Context modelling technique, the assisted living system represents context-aware information based on sensor data. Context-aware information could be temporal information like medical history, spatial information like living area layout, activity structure, end-user profiles, and end-user preferences [28]. Context modelling uses different approaches to represent context information. These approaches include ontology models, situation modelling languages, and key values-based models. The ontology model is significant as it uses hierarchically subclass, superclass, and properties to represent commonly agreed information. Some researchers use online resources like WordNet / e net to deal with incomplete information.

2.3.4. Planning

Automatic Planning and scheduling is an essential factor in the assisted living system for patients with dementia. It guides dementia patients or older adults throughout their daily routine. Voice command, wearable vibrational sensors, and an alarm can remind specific activities per planning and schedule. These activities include medication routine, wakeup call, sleep time, drinking water time, mealtime, etc., which are important to maintain the health of dementia patients and older adults. Some significant techniques used for planning and scheduling are Markov decision processes and hierarchical techniques [29], [78]. Machine learning is also used for planning and scheduling complex living patterns.

2.3.5. Location and Identity Identification

In an assisted living system, location and identity identification of incapacitated and older adults is essential to maintain their privacy and safeguard. This technique tracks, monitors, and fine-grained the location of older adults. For the outdoor positioning of older adults, GPS can be used. But for indoor positioning of older adults, GPS cannot be used due to its accuracy limitations. Hence Indoor positioning smartly uses sensors like smart tiles, PIR sensors, RFID, and ultrasonic sensors to detect the presence of older adults. Machine learning is used to learn the daily living pattern of older adults. Machine learning can identify an abnormal living pattern based on created motion model, e.g., sleeping time, wakeup time, medication time, etc. RFID badges & biometric methods like iris recognition and fingerprint recognition are used to identify older adults. [30], [31].

This paper has reviewed significant elements of an assisted living system. Types of the assisted living system, Technological advancements, and ALS techniques are major factors of the assisted living system. In the next section, the paper discusses samples of existing work on ALS types and the discussion findings.

3. Discussion and findings

In this section, the paper illustrates a summary of a few samples of existing published work. It will help to give an idea of algorithms, techniques, applications, electronic hardware, and performance parameters related to each type of ALS. To provide a better overview of work over ALS in the last 25 years, the Authors have tried to select samples with uniqueness and versatility. Samples of existing published work are selected according to different ALS techniques, generations, and years of published work. A discussion of each type of ALS is concluded with the short findings.

It must be noted that these short findings are not only based on samples of published work but also on other referred research papers and studied literature.

3.1. Mobility-Based ALS

Table 4. Shows a summary of a few samples of existing published work on mobility-based assisted living systems. The parameters selected for performance analysis are the

ability to climb several steps, wheelchair speed, staircase angle, and height. Parris Wellman *et al.* [43] designed mobility-based ALS in the form of a wheelchair.

This wheelchair was designed especially for older adults to help them climb staircases. It was able to climb 12 steps at a 30° angle each. The author has not provided any statistical data About wheelchair speed and staircase height. Later Murray J. Lawn et al. [51] designed a more advanced wheelchair. This wheelchair was capable of climbing staircases of 200m in height and 35°angle. Its speed was also measured, which was 20 steps per minute. The ALS implemented by Murray J. Lawn et al. [51] has the edge over ALS by Parris Wellman et al. [43] with greater climbing speed and more staircase angle.

Author Findings: After reviewing mentioned samples of existing work in table.4 and referred research papers on mobility-based ALS, the authors found few research papers on mobility-based ALS. Diseases like osteoarthritis put limitations on the movement of older adults. It's essential to do more research on mobility-based ALS. Authors found future research scope with different perspectives like:

i. Need of research on elderly people transition from bed to a wheelchair, wheelchair to car, and vice versa.
ii. Mobility-based ALS can be converged with localization techniques for indoor and outdoor mapping.
iii. Solar battery chargers can be used for long-range outdoor mobility purposes
iv. Stability of a wheelchair can be considered as a performance parameter in mobility-based ALS.

Table 4. Samples of existing published work on mobility-based AL

Article and Year	Technique	Sensor / Hardware	Application	Algorithm/Classifier	Performance
Parris Wellman et al. [43], 1995	ALS	Optical encoder, Strain gauge.	Staircase Climbing for older adults.	Impedance control algorithm.	The wheelchair: i. Able to climb twelve steps. ii. Able to walk up at 30° ramps.
Murray J. Lawn et al. [51], 2003	ALS	BS2: Single board computer, FT649: Multiplexer.	Staircase Climbing for older adults.	High-step mechanism-control system.	The wheelchair: i. Staircase height:200mm ii. Can climb at a 35° Staircase angle. iii. Staircase climb and descent speed is 20 steps/ minute

Table 5. Samples of existing published work on Wearable sensor-based ALS

Article and Year	Technique	Sensor / Hardware	Application	Algorithm/ Classifier	Performance
Bijan Najafi et al. [76], 2003	Activity recognition	Kinematic sensor	a. Postural transitions i. Lying to sitting. ii. Sitting to lying. iii. Turning the body in bed. b. Sit to stand c. Stand to sit	Wavelet transform	a. Overall sensitivity = 99% Highest accuracy > 99% b. Average Sensitivity: 93% Average Specificity:82% c. Average Sensitivity:82% Average Specificity:94%
A.K. Bourke et al. [39], 2006	Anomaly Detection	Bi-axial gyroscope at waist	Fall detection	Threshold-based algorithm	Specificity at the following thresholds: i. FT1= 97.5% ii. FT1+FT2=99.2% iii. FT1+FT2+FT3= 100%
Piyush Gupta et al. [36], 2013	Activity recognition	Accelerometer	Jump, run, walk, and sit posture transitions.	Relief-F/ SFFS wrapper algorithm.	Overall accuracy: 98%

Chun Zhu et al. [60], 2015	Anomaly Detection	Motion sensor nodes	Anomaly detection	Maximum likelihood detection	At Threshold = 0.04 i. Recall = 100% ii. Precision = 95.7% iii. F1 Score = 0.1747
Anandarup Mukherjee et al. [64], 2019	ALS	Single-channel electroencephalograph system	Home appliances control	Select-1 Select-M, SILO: Single Lock	The data rate is constant in ASYNC mode, and the delay is high compared to SYNC mode.

3.2. Wearable sensor-based ALS

Table.5 shows a summary of a few samples of existing published work on wearable-based ALS. Performance parameters used by respective authors are Sensitivity, accuracy, and specificity. Bijan Najafi *et al.* [76] designed an ambulatory system for older adults. Here accelerometer was used as a sensor. This system is used to identify Activity transitions of older adults. For different postural transitions, Overall Sensitivity was 99%, and the highest accuracy was more than 99%. The average Sensitivity and specificity in the sit-to-stand transition were 93 percent and 82 percent, respectively. The average Sensitivity and specificity for the stand-to-sit transition were 82 percent and 94 percent, respectively. A.K. Bourke *et al.* [39] used a Bi-axial gyroscope at the waist as a wearable device to identify fall detection. In this paper, the authors used “the resultant Angular velocity (FT1), angular acceleration (FT2), and change in trunk angle signals (FT3)” as thresholds in a threshold-based algorithm. The highest specificity (100%) is achieved at combined FT1, FT2, and FT3. Piyush Gupta *et al.* [36] utilized a tri-axial accelerometer to recognize activities. Here authors implemented an activity recognition and postural transition recognition system with an overall accuracy of 98%. Chun Zhu et al. [60] designed an anomaly detection system with motion sensor nodes and a maximum likelihood algorithm. The authors achieved 100 % Recall, 95.7% Precision, and a 0.1747 F1 Score for the respective system. Anandarup Mukherjee et al. [64] designed a home appliance control system using a single channel electroencephalograph. Here authors used ASYNC and SYNC modes for system operation. In ASYNC mode, the data rate is constant throughout the 1 to 10-meter distance compared to the SYNC mode. In SYNC mode data rate start to reduce after a 6-meter distance. But delay is higher in ASYNC mode as compared to the SYNC mode.

Author Findings

After reviewing mentioned samples of existing work in table.5 and referred research papers on Wearable sensor-based ALS, it is observed that despite good accuracy, wearable sensor-based ALS has some drawbacks. Authors found future research scope like:

i. Wearable sensor-based ALS inhibits the everyday activities of the elderly. Hence the weight of wearable sensor-based ALS must be addressed as a quality parameter.
ii. Radiation at wireless sensor networks must be evaluated against the health parameters.
iii. Internet of things can be integrated to explore wearable sensor-based ALS in the telemedicine facility.
iv. User compatibility with wearable sensors must be evaluated and researched.

3.3. Smartphone-based ALS

Table.6 depicts a summary of a few samples of existing published work on the smartphone-based assisted living system. Performance parameters used by respective authors are Sensitivity, accuracy, specificity, recall, and precision. Nicole A. Capela et al. [33] used an accelerometer integrated with a smartphone for activity recognition. With a threshold Based algorithm, the authors achieved 86.35 % average sensitivity and 97.5 % specificity for sit, stand, and lying positions. The highest 95.95 % sensitivity was achieved for the Stand position, and the highest 100 % specificity was achieved for the Lie position. Adriano Mancini et al. [63] designed assisted living system for the localization of impaired people using a smartphone. The authors performed seven tests in building and urban scenarios. As shown in the table.6, the authors achieved the highest 88.85% average accuracy in the building scenario using Sonar and LiDAR. And an urban scenario, 75.28% average accuracy was achieved using MRR radio. Po-Chou Liang et al. [62] used a Bluetooth sensor in smartphones for indoor localization of patient movement. With the RSSI algorithm, the average estimation error of localization was 0.47 meters at 54 square meters of office. Rong- Kuan Shen et al. [68] created an assisted living system to predict falls. In this system, the authors used the G-Sensor of a smartphone for a different type of fall prediction. The authors achieved 91.64% average recall and 78.55% precision for mentioned events.

Panagiotis Tsinganos et al. [42] used a KNN Classifier for smartphone-based anomaly detection. The authors achieved 95.52% Sensitivity, 97.07% Specificity, and 91.83% Precision for fall detection. Ali Chelli et al. [44] Implemented and evaluated different algorithms for fall detection and activity recognition. For anomaly detection, the authors used an artificial neural network, K-nearest neighbors, a Quadratic support vector machine, and Ensemble bagged tree classifiers. Here QSVM classifier achieved the highest 96.1% accuracy.

Author Findings

After reviewing mentioned samples of existing work in table.6 and other referred research papers on Smartphone-based ALS, the Authors observe some future research scope and findings like:

i. In this ALS type, it's mandatory to carry a smartphone all the time. It may not be possible for older adults.
ii. There is also the possibility of forgetting a smartphone due to the weakened memory of older adults.
iii. To overcome the drawback mentioned above, converged technology needs to converge two or more types of ALSs to form the third generation ALS
iv. The Special design of Smartphone-based ALS for older adults can be introduced into the market.

3.4. Smart home-based ALS

Table.7 Illustrates the performance analysis of Smart home-based ALS. Performance parameters used by respective authors are Sensitivity, accuracy, specificity, precision, and recall. Henry Rimminen et al. [52] used a floor sensor to detect falls in older adults. This system includes three algorithms.

Table 6. Samples of existing work based on Smartphone-based ALS

Article and Year	Technique	Sensor/ Hardware	Application	Algorithm/ Classifier	Performance
Capela *et al.* [33], 2015	Activity recognition	Accelerometer	Stand, Sit, Lie	Threshold based algorithm	For Elderly People a. Avg. Sensitivity: i.Stand: 95.95%, ii. Sit: 68.4% iii. Lie: 94.7% b. Avg. Specificity: i. Stand: 93%, ii. Sit: 99.5%, iii. Lie: 100%
Mancini *et al.* [63], 2015	Localization	Ultrasound, LiDAR, 77 GHz Mid-range automotive radar.	Point-to-point navigation for impaired people	SLAM (Simultaneous localization And mapping) algorithm.	Average overall accuracy using seven tests: a. Building scenario i. Sonar: 57.57% ii. LiDAR: 84.28% iii. Sonar+LiDAR: 88.85% b. Urban Scenario MRR Radio: 75.28%
Po-Chou Liang *et al.* [62], 2016	Localization	BLE (Bluetooth low energy) sensor	Real-time indoor patient movement pattern Tele-monitoring	RSSI (Received signal strength indication)	The average estimation error is 0.47 meters at 54 square meters of office.
Rong-Kuan Shen *et al.* [68], 2016	Anomaly Detection	G-Sensor	Fall Prediction	High-level fuzzy Petri net (HLFPN)	Event / Recall / Precision Forward fall 91.60% 78.57% Backward fall 87.50% 77.78% Sideway fall 95.83% 79.31%
Tsinganos *et al.* [42], 2017	Anomaly Detection	Accelerometer	Fall detection	KNN Classifier	i. Sensitivity: 95.52% ii. Specificity: 97.07% iii. Precision: 91.83%
Ali Chelli *et al.* [44], 2019	Anomaly Detection	Accelerometer	Fall detection	KNN, ANN, QSVM, EBT	Overall Accuracy: KNN: 85.8%, ANN: 91.8%, QSVM :96.1%, EBT:85.8%

These three algorithms are near field imaging, Marker chain, and Bayesian filtering. Experimentation over the proposed system achieved 91 % of Sensitivity and specificity. Feng Zhou et al. [32] designed converged technology comprised of Smart home and Wearable sensor-based ALS. It is a context-aware system implemented to track 20 everyday activities of older adults. This system achieved 92% of average precision and recall. H. Ghayvat et al. [61] innovated a wellness sensor protocol to monitor multiple appliances used by the users at Smart homes. This system can predict end users' wellness according to the usage of smart home appliances. The proposed system reduced requirement of storage and data by 60 to 72 % compared to the Zigbee protocol. Nour Eddin Tabbakha et al. [59] created a motion tracking and indoor positioning system

The proposed system used four classifiers for the elderly in a smart home setting. Amongst four classifiers Support vector machine was found highly efficient for indoor localization with 99% accuracy. At the same time, Random Forest achieved the highest accuracy of 99.97% for motion tracking. George Oguntala introduced the Smart Wall framework for human activity recognition. This system used an RFID tag with a multivariate Gaussian algorithm. The implemented system was evaluated using twelve real-time human activities. The proposed algorithm showed 97.9% accuracy. Pubali De et al. [57] have implemented MCP and modified MCP with the IRLS method for indoor detection of human motion in eight directions. A proposed system K-SVD is used as a dictionary machine learning algorithm.

f existiTable 7. Samples ong published work on Smart home-based ALS

Article and Year	Technique	Sensor	Identified Activities	Algorithm/Classifier	Performance
H. Rimminen *et al.* [52], 2010	Anomaly Detection	NFI (Near field imaging) floor sensor	Fall Detection	Near field imaging, Markov chain, Bayesian filtering	Sensitivity: 91% Specificity: 91 %
F. Zhou *et al.* [32], 2011	Context modelling	Temperature, humidity, lighting sensor	20 Activities of daily living.	A Case-Driven Ambient Intelligence.	Avg. precision: 92 % Avg. recall: 92 %
Ghayvat *et al.* [61], 2015	ALS	Temperature, PIR, Force, Electronic & Electrical appliances sensing unit.	Predicting wellness of users by monitoring usage of appliances.	Intelligent sampling and transmission control algorithm.	Data storage was reduced by 60 % to 72 %.
Tabbakha *et al.* [59], 2017	Localization	Motion sensor	Indoor localisation of elderly people	Support vector machine, K-NN, Decision trees, Random forests	Accuracy at: Location tracking: 99%, Motion tracking: 99.97%
Oguntala *et al.* [58], 2017	Activity recognition	RFID Tag	Smart health care using human activity recognition.	Multivariate Gaussian via maximum likelihood estimation	Accuracy: Multivariate Gaussian:97.6% Random Forest: 92.5% Logistic regression: 90% Support vector machine: 94.5%
Pubali De *et al.* [57], 2020	Activity recognition	PIR sensors	Indoor human movement in eight directions	Multiple cluster pursuit (MCP), Iterative-reweighed-least-squares (IRLS), Modified Multiple cluster pursuit (MCP)	Classification accuracy: MCP with IRLS: 90.60%, Modified MCP algorithm with IRLS: 92.01%

MCP with the IRLS method obtained 90.6% classification accuracy. Modified MCP with the IRLS method obtained 92.01% classification accuracy.

Author Findings: After reviewing mentioned samples of existing work in table VII and other referred research papers on Smart home-based ALS, the Authors observe some future research scope and findings like:

i. Smart home-based ALS is an efficient In-house ALS system. It provides the best safety and assistance to elderly People.
ii. There is a need to lower the cost of sensors and electronic devices used in smart home-based ALS. For common elderly people, it's difficult to afford this type of ALS system.
iii. Context-awareness must be addressed to assure the safety and privacy of older adults.
iv. Smart home-based ALS is more efficient with integrating a computer vision system.

Table 8. Samples of existing work on Computer vision-based ALS

Article and Year	Technique	Sensor/ Hardware	Application	Algorithm/ Classifier	Performance
M.Goffredo *et al.* [65], 2009	Activity Recognition	Camera	Sit to Stand in Young & Elderly	Gauss - Laguerre transform	Sit to stand parameter analyzed with ANOVA: Group / Angle (Deg) / P value Young / 64.1 ± 7.1 / < 0.001 Elderly / 75.2 ± 5.7 / < 0.001
X. Ma *et al.* [66], 2014	Anomaly Detection	Low-cost depth camera	Fall detection	Extreme learning machine (ELM) classifier	i. Specificity: 77.14% ii. Sensitivity: 91.15% iii. Accuracy: 86.83%
J Rafferty *et al.* [41], 2016	Anomaly Detection	Thermal vision sensor	Fall detection	Fall detection process	i. Accuracy: 68% ii. Average Sensitivity: 68.35% iii. Average specificity: 75%
Hbali *et al.* [54] , 2017	Activity Recognition	3D depth sensor Microsoft kinect	Human activity recognition for elderly	Extremely randomized trees algorithm	i. MSR Daily activity 3D dataset: 73.43% (Maximum accuracy) ii. MSR 3D action dataset: 92.18 % (Maximum average accuracy)
Chaudhary *et al.* [37], 2018	Anomaly Detection	Video camera	Anomalous activity detection	Gaussian mixture model	Accuracy up to 90%
Guo *et al.* [56], 2019	ALS/Gait monitoring	RGB-D sensor	Pose estimation, Recognition of abnormal gaits.	Simultaneously localization and mapping (SLAM)	Classification accuracy: Methods / Intra Subject / Cross Subject / LOSO SVM-GT / 99.31% / 76.77% / 85.15%

3.5. Computer vision-based ALS:

Table.8 illustrates the performance analysis of Computer vision-based ALS. Performance parameters used by respective authors are Sensitivity, accuracy, specificity, and P-value in the ANOVA technique. Michela Goffredo et al. [65] implemented a marker-less computer vision technique using the Gauss-Laguerre transform. Here Sit to Stand (STS) is analyzed in clinical contexts. The proposed system applied to two groups of people: young and elderly. Performance analysis is done with the ANOVA technique. The p-value is a probability. It is used to evaluate how likely the proof is to be rejected by the null hypothesis. Lower probabilities indicate stronger evidence against the null hypothesis. STS is analyzed over the different angles of movement.

It has shown good results for all angles. It is found that the p-value of the ANOVA technique is less than 1% at an angle of 64 ± 7.1 degrees for the youngsters' group and 75.2 ± 5.7 degrees for the elderly group. Xin Ma *et al.* [66] used a low-cost depth camera to detect falls of older adults. The proposed system used an extreme learning machine classifier. For experimentation purposes, six actions of ten subjects are evaluated. Implemented approach achieved 77.14% specificity, 86.83% accuracy and 91.15%

sensitivity. Joseph Rafferty *et al.* [41] implemented a fall detection system using thermal vision sensing. During the experiment, a thermal vision sensor was deployed 4 hours to monitor a subject. The proposed system achieved 68% accuracy, 68.35% average sensitivity, and 75% average specificity. Youssef Hbali *et al.* [54] used 3 D depth sensor with an extremely randomized trees algorithm for the elderly monitoring system. Minkowski and cosine distance between 3 D joints are key features in the proposed algorithm. The proposed approach achieved a maximum of 73.43 % accuracy in MSR daily activity and a maximum of 92.8% average accuracy in MSR 3D action. Sarita Chaudhary *et al.* [37] designed multiple anomalous activity detection systems using a video camera. The proposed system detected walking, crawling, and running activity in a single video. Speed, centroid, direction, and dimensions are key to detecting the activities. This system has achieved an accuracy of up to 90 %. Yao Guo et al. [56] used the RGB-D camera for pose estimation and abnormal gait recognition. The proposed system was evaluated against six gait patterns done by sixteen volunteers.

Three protocols are used to evaluate classification accuracy, leaving one subject out (LOSO), Intra subject, and Cross subject. In the proposed framework highest recognition rate of 99.31% is achieved under intra-subject protocol with the support vector machine (SVM-GT) method.

Author Findings:

After reviewing mentioned samples of existing work in table.8 and other referred research papers on Computer vision-based ALS, the Authors observe some future research scope and findings like:

i. Working with computer vision-based ALS has a broad scope. Integration of artificial intelligence with computer vision can exhibit higher accuracy with cost-effective implementation.
ii. Computer vision-based ALS implemented at the special-purpose machine can be a game-changer in the field of the assisted living system. It can be used as an Indoor and outdoor electronic device.
iii. Computer vision-based ALS can bring down the cost of ALS due to its low-cost accessories compared to other ALS types.
iv. Privacy safeguard of older adults is a major concern in computer vision-based ALS. It must be researched on a priority basis.

In the next section, based on the Review and short findings of each type of ALS, the authors tried to draw an overall conclusion and future direction in ALS.

4. Conclusion

In the last 25 years assisted living system has shown significant technological advancement. All three ALS generations successfully unleashed the power of technologies for the well-being of incapacitated and older adults. The third generation of ALS has integrated most of the features of older generations, making it superior. But still, there are prominent challenges that must be tackled:

4.1. Power harvesting

There is a large research scope for power harvesting in ALS as it directly impacts wearable sensors and devices' carrying capability. An efficient wireless power transmission system must have tiny and durable power sources.

4.2. Privacy issues

Very few authors take privacy issues on a priority level in the ALS framework. Third-generation ALS has reached its top technical level, where privacy issues must be addressed as an independent design entity. ALS must not be intrusive. There must be differently designed levels of ALS application to safeguard user privacy. Context modelling can also play a key role in privacy safeguard.

4.3. User compatibility and awareness

ALS design must be compatible with the end-user for wearing and handling comfort. Efforts should be taken to increase public awareness of ALS. Training and information sessions for users may increase the popularity of ALS. Increased use of ALS will provide multiple end-users feedback to improve the existing system.

4.4. Converged technology

The use of converged technology may integrate the best of the best technology to give a cost-effective, efficient, and user-friendly ALS solution to older adults.

4.5. Legal framework

Legal framework must safeguard consumer rights by addressing the usability and complexity of ALS. There is the requirement of structured regulation for ALS deployment. Users must be aware of these regulations.

4.6. Real-world application

Most of the published work is designed for indoor applications. There is large scope for outdoor application research. These applications have to be improved and evaluated in the real-world application scenario.

References

[1] Ministry of Statistics and Programme Implementation, Government of India, Elderly in India, report, (2016).
[2] Department of Economic and Social Affairs Population Division United Nations, World population ageing, report, (2015).
[3] Siew Kwaon Lui et al., Elderly Stroke Rehabilitation: Overcoming the Complications and Its Associated Challenges, Hindawi, Current Gerontology and Geriatrics Research, (2018) 01-09.
[4] K. Subramanya, et al., Surface Electrical Stimulation Technology for Stroke Rehabilitation: A Review of 50 Years of Research, American Scientific Publishers, Journal of Medical Imaging and Health Informatics, 2 (2012) 1–14.
[5] Junchi Yan, et al., Design of a Wheelchair with Legs for People with Motor Disabilities, IEEE transactions on rehabilitation engineering, 3 (1995) 343-353.
[6] Ruijiao Li, et al., Cognitive assisted living ambient system: A survey, Digital Communications and Networks, 1(4) (2015) 229-252.
[7] Barry Mirkin, et al. The demography of population ageing, Population Division, Dept. of Economic and Social Affairs, United Nations Secretariat, report, (2000).
[8] Ambient Assisted Living, Accessed on: Jan. 17, (2022). [Online]. Available: https://de.wikipedia.org/wiki/Ambient_Assisted_Living.
[9] M.J. O'Grady, et al., Towards Evolutionary Ambient Assisted Living Systems, Springer,Journal of Ambient Intelligence and Humanized Computing, 1(1) (2009) 15-29.
[10] El MurabetAmina, et al., A novel reference model for ambient assisted living system, Applied computing and informatics, (2018) 01-07.
[11] El Murabet Amina, et al., Ambient assisted living systems models and architectures, Elsevier, Journal of King saud university- Computer and information science, (2018) 01-10.
[12] Ni Zhu, et al., Bridging e-Health and the Internet of Things: The SPHERE Project, IEEE, Intelligent systems, (2015) 39-46.
[13] T. Ishimatsu, et al., Development of a stairclimbing machine in Nagasaki, in Proc. 3rd Int. Workshop Advanced Mechatronics, Kanwon, Korea, (1999) 214–217.
[14] K. J. Waldron, et al., Configuration Design of the adaptive suspension vehicle, Int. J. Robotics Res., 3(2) (1984) 37-48.
[15] Rashidi, P, et al., A Survey on Ambient Assisted Living Tools for Older Adults, IEEE Journal of Biomedical and Health Informatics, (2012) 579-590.
[16] André Rodrigues, et al., iSenior—A Support System for Elderly Citizens, IEEE transactions on emerging topics in computing, (2013) 207-217.
[17] Lingfei Mo, Member, IEEE, et al., Wireless Design of a Multisensor System for Physical Activity Monitoring, IEEE transactions on biomedical engineering, 59(11) (2012) 3230-3237.
[18] El Murabet Amina, et al., Validation Methodologies for RAs: A Case Study of RAFAALS2.0, American Institute of Science,International Journal of Electronic Engineering and Computer Science , 4(1) (2019) 1-9.
[19] Andrew Sixsmith, et al., SOPRANO – An Ambient Assisted Living System for Supporting Older People at Home, springer, International Conference on Smart Homes and Health Telematics, (2009) 233-236.
[20] Peter Wolf, et al., SOPRANO–An extensible, open AAL platform for elderly people based on semantical contracts, European conference on artificial intelligence, (2008).
[21] Marius Mikalsen, et al., Interoperability Services in the MPOWER Ambient Assisted Living Platform,Studies in health technology and informatics , (2009) 366-370.
[22] Elisa Yumi Nakagawa, et al., RAModel: A Reference Model for Reference Architectures, IEEE, Joint Working Conference on Software Architecture & 6th European Conference on Software Architecture, (2012) 297-301.
[23] Francesco Furfari1, et al., The PERSONA Framework for Supporting Context-Awareness in Open Distributed Systems, Springer, European Conference on Ambient Intelligence: Ambient Intelligence, (2008) 91-108.
[24] Juan Carlos Augusto, et al., Ambient Intelligence: Concepts and Applications, Springer, International Conference on Software and Data Technologies, (2006) 16-26.
[25] J. W.S. Liu, et al, Reference Architecture of Intelligent Appliances for the Elderly, in IEEE, Proceedings of the 18th International Conference on Systems Engineering (ISCEng'05), (2005).
[26] Sten Hanke, et al, universAAL – An Open and Consolidated AAL Platform, Springer, Ambient Assisted Living, (2011) 127-140.
[27] Alex Mihailidis, et al., Context-aware assistive devices for older adults with dementia, in Gerontechnology 2(1) (2002) 173-188.
[28] Richard Simpson, et al., Plans and Planning in Smart Homes, Springer, Designing Smart Homes, (2006) 71 – 84.
[29] Varun Chandola, et al., Anomaly Detection: A Survey, ACM journals, ACM Computing Surveys, 41(3) (2009) 1–72.
[30] Roy Want, et al., The Active Badge Location System, ACM transaction on information system, 10(1) (1992) 91-102.
[31] Feng Zhou, et al., A Case-Driven Ambient Intelligence System for Elderly In-Home Assistance Applications, IEEE transactions on systems, man, and cybernetics—part c: applications and reviews, 41(2) (2011) 179-189.
[32] Nicole A. Capela, Edward D Lamaire, Natalie Baddour, Improving Classification of Sit, Stand, and Lie in a Smartphone Human Activity Recognition System, IEEE, International Symposium on Medical Measurements and Applications (MeMeA) Proceedings, (2015).
[33] Francesco Antoniazzi, et al., A Web of Things Approach for Indoor Position Monitoring of Elderly and Impaired People, IEEE, proceeding of the 21st conference of fruct association, (2017) 51-56.
[34] Kyle E.C. Booth, et al., Robots in Retirement Homes: Person Search and Task Planning for a Group of Residents by a Team of Assistive Robots, IEEE, Intelligent systems, (2017) 14-21.
[35] Piyush Gupta, Tim Dallas, Feature Selection and Activity Recognition System Using a Single Tri-axial Accelerometer, IEEE Transactions on Biomedical Engineering, Neural systems and rehabilitation engineering, 61(6) (2014) 1780-1786.
[36] Sarita Chaudharya, Mohd Aamir Khana, Charul Bhatnagar, Multiple Anomalous Activity Detection in Videos, Elsevier, in 6th International Conference on Smart Computing and Communications, (2017) 336-345.

[37] Lionel M. Ni, Yunhao Liu, Abhishek Patil, LANDMARC: Indoor Location Sensing Using Active RFID, in Kluwer Academic Publishers, Conference in Wireless Networks, (2004) 701–710.
[38] A. K Bourke, G.M.Lyons, A threshold based fall detection algorithm using biaxial gyroscope, Elsevier, Medical engineering and physics, (2008) 84-90.
[39] I Putu Edy Suardiyana Putra, et al., An Event-Triggered Machine Learning Approach for Accelerometer-Based Fall Detection, MDPI, Sensors, (2017) 1-18.
[40] Joseph Rafferty, et al., Fall Detection through Thermal Vision Sensing, Springer, Ubiquitous Computing and Ambient Intelligence, (2016) 84-90.
[41] Panagiotis Tsinganos, Athanassios Skodras , A Smartphone-based Fall Detection System for the Elderly, In IEEE,10th International Symposium on Image and Signal Processing and Analysis (ISPA 2017) , (2017) 53-58.
[42] Parris Wellman, et al., Design of a Wheelchair with Legs for People with Motor Disabilities, in IEEE, IEEE transactions on rehabilitation engineering, 3(4) (1995) 343-353.
[43] Ali Chelli, Matthias Patzold, A Machine Learning Approach for Fall Detection and Daily Living Activity Recognition, IEEE Access, (2019) 1-17,2019.
[44] Erina Ferro, et al., The UniversAAL Platform for AAL (Ambient Assisted Living), in De Gruyter,J. Intell. Syst., (2015) 1-19.
[45] Peter Brown, OASIS-Reference Architecture Foundation for Service Oriented Architecture Version 1.0, (2012) 1-118.
[46] Continua Design Guidelines, Accessed on: Jan. 17, 2022. [Online]. Available: http://www.pchalliance.org/continua-design-guidelines
[47] Henri Hietala, VeikkoIkonen, Feelgood – Ecosystem of PHR based products and services, (2009) 1-68.
[48] Francesco Furfari1, et al., The PERSONA Framework for Supporting Context-Awareness in Open Distributed Systems, Springer, Ambient Intelligence, (2008) 91-108.
[49] Sten Hanke, et al., A need for an interoperable open-source middleware for ambient assisted living applications, in Proceedings of the Third International Conference on Health Informatics, (2010) 517-524.
[50] Murray J. Lawn, et al., Modeling of a Stair-Climbing Wheelchair Mechanism with High Single-Step Capability, IEEE transactions, neural systems and rehabilitation engineering, 11(3) (2003) 323-332.
[51] Henry Rimminen, et al., Detection of Falls Among the Elderly by a Floor Sensor Using the Electric Near Field, IEEE transactions on information technology in biomedicine, 14(6) (2010) 1474-1476.
[52] Rita Cucchiara, et al., Probabilistic Posture Classification for Human-Behavior Analysis, IEEE transactions on systems, man, and cybernetics—part a: systems and humans, 35(1) (2005) 42-54.
[53] Youssef Hbali, et al., Skeleton- based human activity recognition for elderly monitoring systems, IET Computer Vision., 12(1) (2018) 16-26.
[54] Bijan Najafi, et al., Ambulatory System for Human Motion Analysis Using a Kinematic Sensor: Monitoring of Daily Physical Activity in the Elderly, IEEE transactions on biomedical engineering, 50(6) (2003) 711-723.
[55] Yao Guo, et al., 3-D Canonical Pose Estimation and Abnormal Gait Recognition with a Single RGB-D Camera, IEEE Robotics and Automation Letters, 4(4) (2019) 3617-3624.
[56] Pubali De, et al., PIR Sensor based AAL Tool for Human Movement Detection: Modified MCP based Dictionary Learning Approach, IEEE Transactions on Instrumentation and Measurement, 69(10) (2020) 7377 – 7385.
[57] George A. Oguntala, et al., SmartWall: Novel RFID-Enabled Ambient Human Activity Recognition Using Machine Learning for Unobtrusive Health Monitoring, IEEE Access, 7 (2019) 68022-68033.
[58] Nour Eddin Tabbakha, Wooi-Haw Tan, Chee-Pun Ooi, Indoor location and motion tracking system for elderly assisted living home, in IEEE, International Conference on Robotics, Automation and Sciences (ICORAS), (2017).
[59] Chun Zhu, Weihua Sheng, Meiqin Liu, Wearable Sensor-Based Behavioral Anomaly Detection in Smart Assisted Living Systems, IEEE Transactions on Automation Science and Engineering, 12(4) (2015) 1225 – 1234.
[60] H.Ghayvat, J.Liu, S.C.Mukhopadhyay, Wellness SensorNetworks: A Proposal and Implementation for Smart Home for Assisted Living, IEEE sensors journal, 15(3) (2015) 1321-1329.
[61] Po-Chou Liang, Paul Krause, Smartphone-based Real-time Indoor Location Tracking with One-meter Precision, IEEE Journal of Biomedical and Health Informatics, (2015) 1-6.
[62] Adriano Mancini, Emanuele Frontoni, Primo Zingaretti, Embedded Multisensor System for Safe Point-to-Point Navigation of Impaired Users, IEEE Transactions on intelligent transportation systems, (2015) 1-13.
[63] Anandarup Mukherjee, Sudip Misra, Abhay Atrish, MiND: Mind Networked Device Architecture for Attention-Gated Ambient Assisted Living Systems, IEEE systems journal, (2019) 1-7.
[64] Michela Goffredo et al., Markerless Human Motion Analysis in Gauss–Laguerre Transform Domain: An Application to Sit-To-Stand in Young and Elderly People, IEEE Transactions on information technology in biomedicine, 13(2) (2009) 207-216.
[65] Xin Ma, et al., Depth-Based Human Fall Detection via Shape Features and Improved Extreme Learning Machine, IEEE Journal of biomedical and health informatics, 18(6) (2014) 1915-1922.
[66] Pollack ME., Planning Technology for Intelligent Cognitive Orthotics, in 6th International Conference on AI Planning and Scheduling, (2002) 322-331.
[67] Rong-Kuan Shen, et al., A Novel Fall Prediction System on Smartphones, IEEE Sensors Journal, 17(6) (2017) 1865 – 1871.
[68] D. Bryant and B. R. Bryant, Assistive Technology for People with Disabilities, Allyn and Bacon, Boston, MA, (2003).
[69] K. Doughty, K. Cameron, and P. Garner, Three generations of telecare of the elderly, J. Telemed. Telecare, (1996) 71-80.
[70] A. Sixsmith, G. Gibson, R. D. Orpwood and J. M. Torrington, New technologies to support independent living and quality of life for people with dementia, Alzheimer's Care Q. 7, (2007) 194–202, 2007.

[71] Stephanie Blackman, Claudine Matlo, Charisse Bobrovitskiy, Ambient Assisted Living Technologies for Aging Well: A Scoping Review, De Gruyter, J. Intell. Syst., 25(1) (2016) 55–69.
[72] A. Sixsmith, An evaluation of an intelligent home monitoring system, J. Telemed. Telecare, (2000) 63–72.
[73] Chin Teck Ng, Osteoarthritis and falls in the older person, Age and Ageing, (2013) 561–566.
[74] Chandra Prakash Pal, Epidemiology of knee osteoarthritis in India and related factors, Springer, Indian J Orthopedics, 50(5) (2016) 518–522.
[75] Bijan Najafi, Ambulatory System for Human Motion Analysis Using a Kinematic Sensor: Monitoring of Daily Physical Activity in the Elderly, IEEE transactions on biomedical engineering, 50(6) (2003) 711-723.
[76] Stephen D. Anton, et al., Successful aging: Advancing the science of physical independence in older adults, Ageing Research Reviews, (2015) 304-327.
[77] Mohamad Rahhal, et al., Health of Humans and Machines in a Common Perspective, Elsevier, Procedia Computer Science, (2020) 415-422.
[78] Saleem Ahmed, Security and Privacy in Smart Cities: Challenges and Opportunities, International Journal of Engineering Trends and Technology , 68(2) (2020) 1-8.